

Regression

I. Motivation

In this experiment we perform polynomial fitting for a given 1-d and 2-d data. Both least squares and ridge regression is performed. First we train the model with training data and then tune the hyper-parameters (polynomial degree and regularisation parameter) with the development data.

II. 1-D data

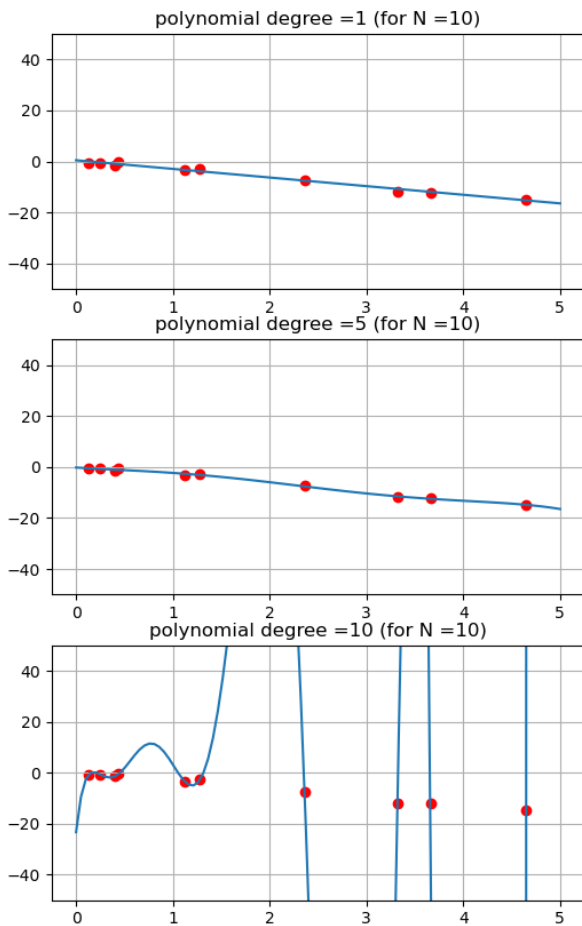


Fig. 1. For 10 data points

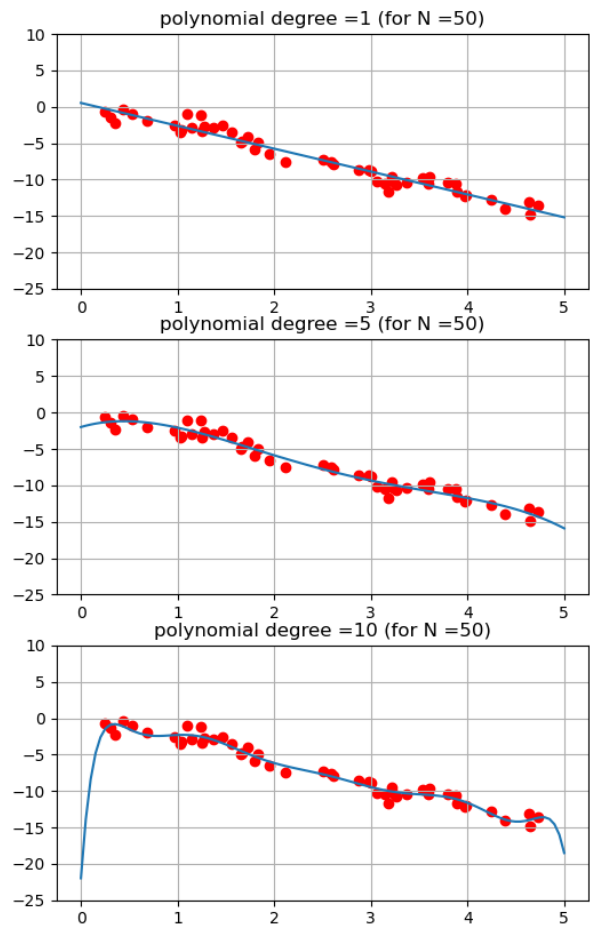


Fig. 2. For 50 data points

Inferences from Fig 1-4:

1. With increasing polynomial degree or model complexity, we observe over-fitting.
2. For the same model complexity, increasing the number of data points results in reduction of the over-fitting problem.

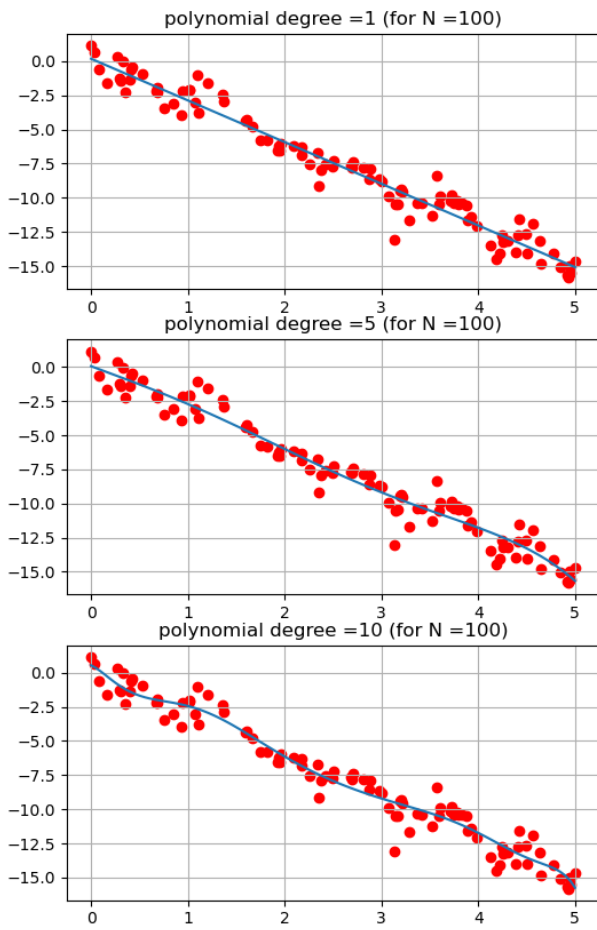


Fig. 3. For 100 data points

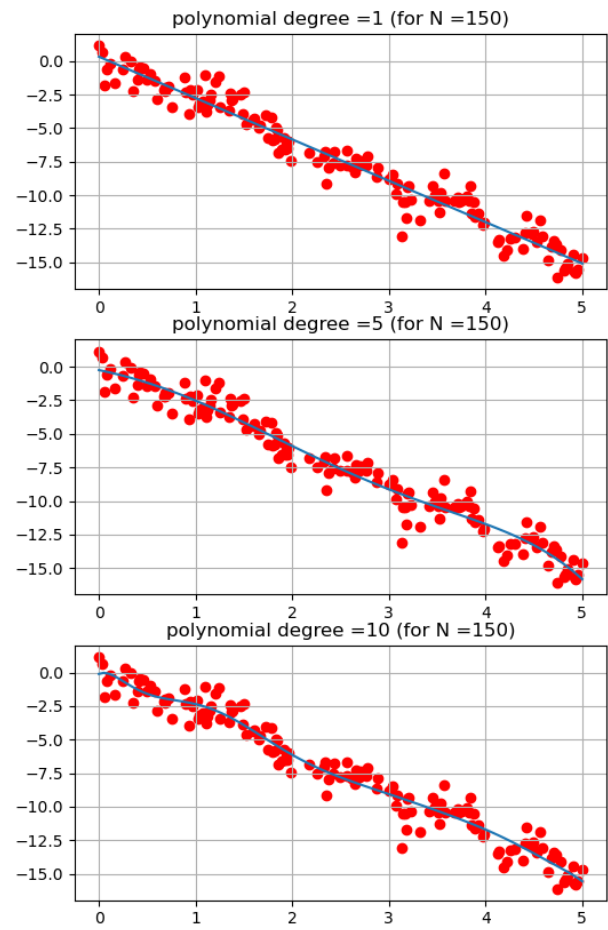


Fig. 4. For 150 data points

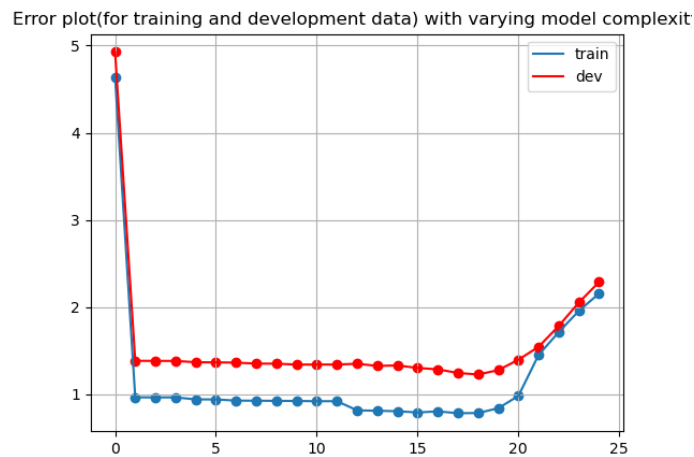


Fig. 5. Error plot

We have optimal degree as 18. Let us try ridge regression for this model.

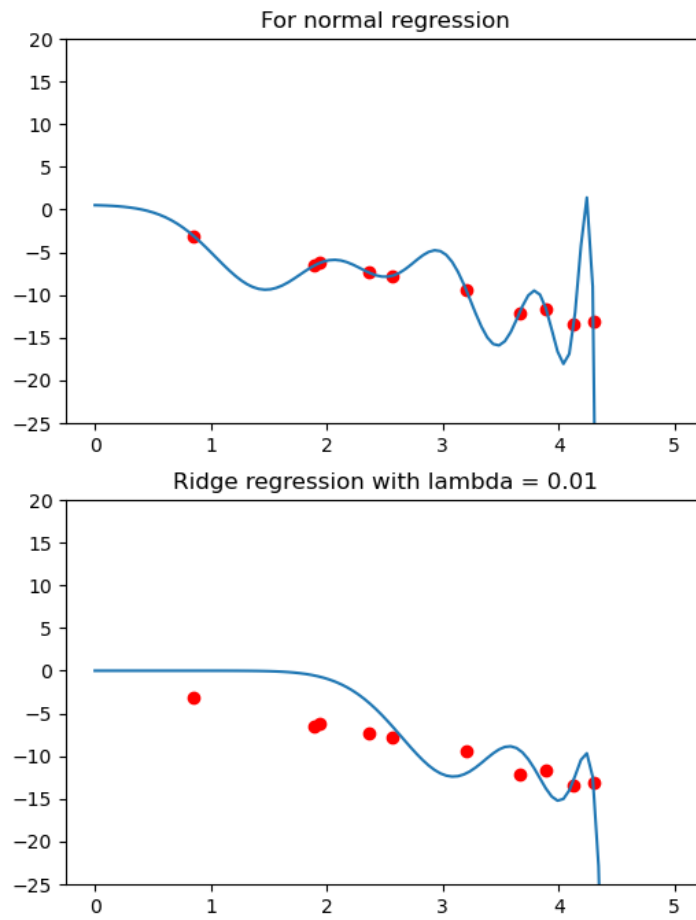


Fig. 6. *Ridge regression*

From fig-6, we can observe that by adopting ridge regression, over-fitting is reduced.

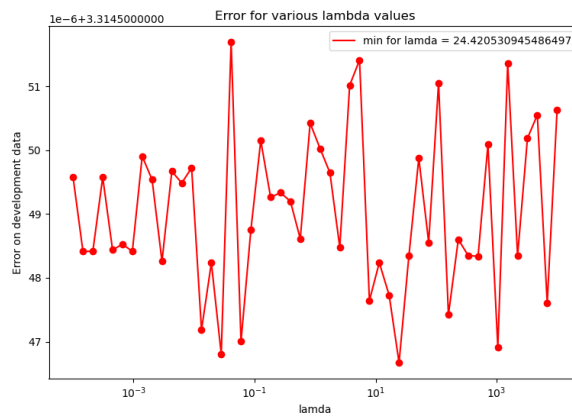
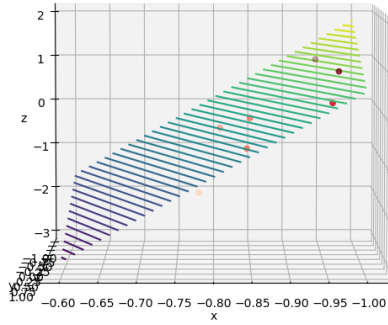


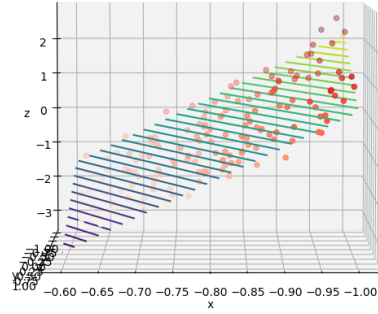
Fig. 7. *Finding optimal Lambda*

III. 2-D data

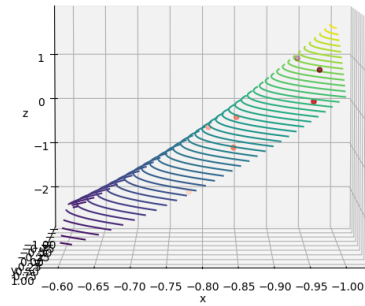
polynomial degree =1 (for N =10)



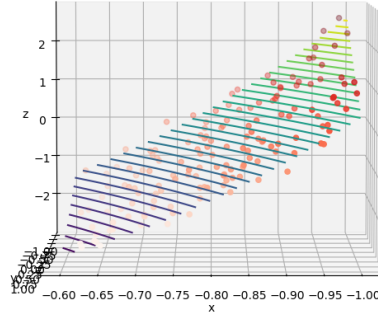
polynomial degree =1 (for N =150)



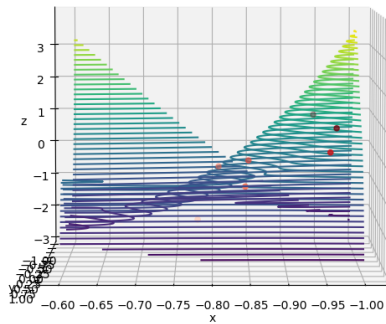
polynomial degree =2 (for N =10)



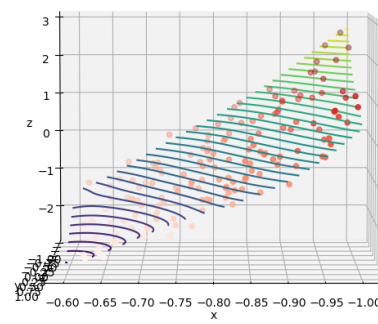
polynomial degree =2 (for N =150)



polynomial degree =5 (for N =10)



polynomial degree =5 (for N =150)



Same inferences as in the 1-d case apply for the above figures too. Increasing model complexity reinforces over-fitting. For the same model complexity, increasing the number of data points reduces over-fitting.

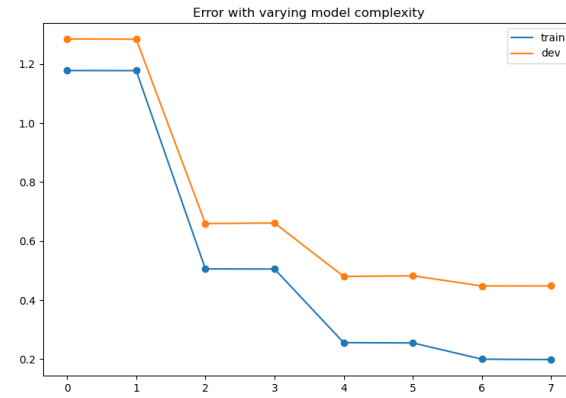


Fig. 8. *Error plot*

We have optimal degree=6 or 7. Applying ridge regression on the model with degree=7.

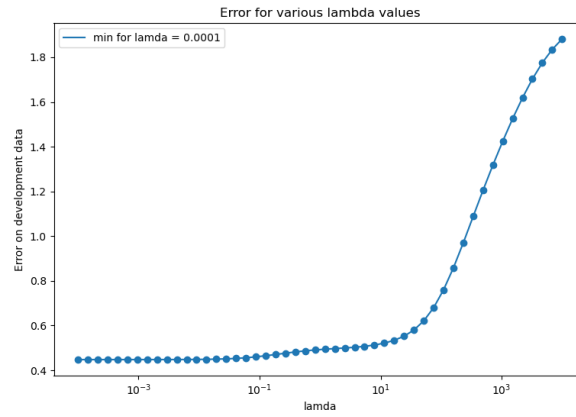


Fig. 9. *Finding optimal Lambda*